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Optimization of Process Parameters in Turning Operation of Aluminium (6061) with Cemented Carbide Inserts Using Artificial Neural Network

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ABSTRACT: Surface roughness quality of material plays a vital role in its performance standards and Fatigue Life. The process parameters which are considered while calculating the surface roughness are speed, feed, and depth of cut. This paper examines the parameters that affect the roughness of the surface produced during the process of turning on Aluminium 6061. In this study, the experimental design is analyzed using the neural network tool. The relationship between the turning parameters on the surface roughness is investigated using two back Propagation algorithms. Simulation Tool is used to predicting the results of surface roughness and the obtained results are compared to the results obtained by Taguchi's method and it is observed that ANN tool delivered an accuracy of 7.47% more than that of Taguchi while predicting results.

Keywords: Aliminium (6061), Cemented Carbide

I. INTRODUCTON

Surface Roughness plays a huge role in the quality of a material and its performance during the machining operations. For attaining the best quality surface roughness optimum cutting parameters needs to be analyzed. The optimization of various cutting parameters with surface roughness is highly complex and non-linear. Artificial Neural Network (ANN) models have served efficiently in predicting outputs of complex data relations by imitating the biological features of neurons of the human body. ANN performs simulation with help of the data it is trained with, the data for the training is obtained experimentally and the more the data for training will be available the less shall be the error in the predicted values. An ANN model can be created using the back-propagation technique for the simulation of the process and its parameters. It can be then used to predict the output values, with the assurance of low error in the predicted value versus the experimental values, it can be used for optimization.

A. Artificial Neural Network

Artificial neural networks are inspired by the biological system of neurons in the human body and have been efficient in providing prediction for non-linear information. ANN comprises nodes or units called artificial neurons. Each neuron can transmit signals to other neurons, hence exhibiting features of those of the biological arrangement of human body neurons.

ANN has the following three components which are essential for a model to be created:

1. Network Architecture: It is the arrangement/ design of neurons in various layers along with defining the characteristics they will possess. In this study, we are going to use the Feed Forward Type.

2. Training: Each neuron exhibits its characteristics. Weights help in defining/modifying these characteristics, training is used to modify these weights between network layers to obtain the desired output.

3. Learning Rule: It is a method or a defined mathematical logic that improves the ANN's performance and applies this given rule over the whole network. Thus it updates the weights and bias (according to the given logic) of a network when a network is being trained in a specific data environment. Examples can be the Delta learning rule, Hebb's learning, Perceptron learning rule, etc.

4. Activation Rule: The activation Rule is a local Method/ procedure that each neuron follows in updating its activation concerning the input from neighboring neurons. Following are the types of activation functions:

1. Threshold function,

2. Piecewise-linear function,

3. Sigmoid function. (Its graph is an s-shaped graph, which is by far the most commonly used form of the activation function.)

B. Neural Network Tool in MATLAB

MatLab is a Computer language and computational mathematics environment developed by MathWorks used to process complex mathematical operations and manipulation of various forms of data including matrices, arrays, variables, etc.

Neural Network Toolbox (NN tool) is an inbuilt tool that provides the neural network developing framework in MatLab which can be used further for the modeling of complex nonlinear systems that can not be not easily modeled with a closed-form equation. The toolbox can be used to perform the following operations on a neural network

1. Design,

2. Train,

3. Visualize,

4. Simulate neural networks.

We can use Neural Network Toolbox for applications such as clustering, pattern recognition, time-series prediction, and dynamic system modeling and data fitting. It supports a variety of training algorithms including but not restricted to

1. Gradient descent methods,

2. Conjugate gradient methods,

3. The Levenberg-Marquardt algorithm (LM), and the

4. Resilient Backpropagation algorithm (Rprop).

The toolbox helps us quickly modify the network and weights related to it. Error weight can be defined according to the relative role they play in the desired output. The Toolbox also provides a regression plot for visualization of the weights that the network followed and leaves it to the user if or not the network needs to be retrained.

B. Network design steps

The following are some standard steps involved in the making of a neural network to solve the problem in the application areas of time-series analysis, clustering, function fitting, and pattern recognition.

1. Data Collection

2. Network Creation

3. Network Definition

4. The initialization of the weights and biases

5. Training the network

6. Validating the network

Steps involved in Matlab NN tool:

1. Import the data into the MATLAB Workspace, experimentally obtained data should be stored in Target and process parameter values in Input

2. In the common window, nntool shall be typed which will lead to a separate window, input the target and input values into the data manager

3. Then click on the NEW button to create a new network, and define the network properties and layer properties accordingly, and then proceed to create it

4. Open the network and select training parameters, in Input import Input, and Target import Target.

5. Start training the network, until the desired regression graph is achieved

6. Simulation can be performed in the simulation tab using sample values.

7. Export all values to the MATLAB workspace.

II. DATA ANALYSIS & MODELLING OF NETWORK

1. Data collection

The data was collected from the study "Optimization of Process Parameters in Turning Operation of Aluminium (6061) with Cemented Carbide Inserts Using Taguchi Method and ANOVA"

Following data was collected:

Parameter and parameter levels:

Table 1: Composition of Al alloy (2)

Element	**Weight**
Cu	0.15-0.4
Mg	0.7-1.2
Si	0.4-0.8
Fe	0.7 max
Mn	0.2-0.8
Other	0.4

Table 2: Cutting Parameters that were used (2)

S. No.	Parameter	Stage1	Stage2	Stage3
A	**Feed (mm/rev)**	0.15	0.125	0.100
B	**Speed (RPM)**	2100	1900	1700
C	**Depth of cut (mm)**	0.4	0.3	0.2

2. Data Modelling and Analysis

A Neural Network is created using the NNTOOL in MatLab. Training parameters and the methodology used in the NN Tool are given in the following figures

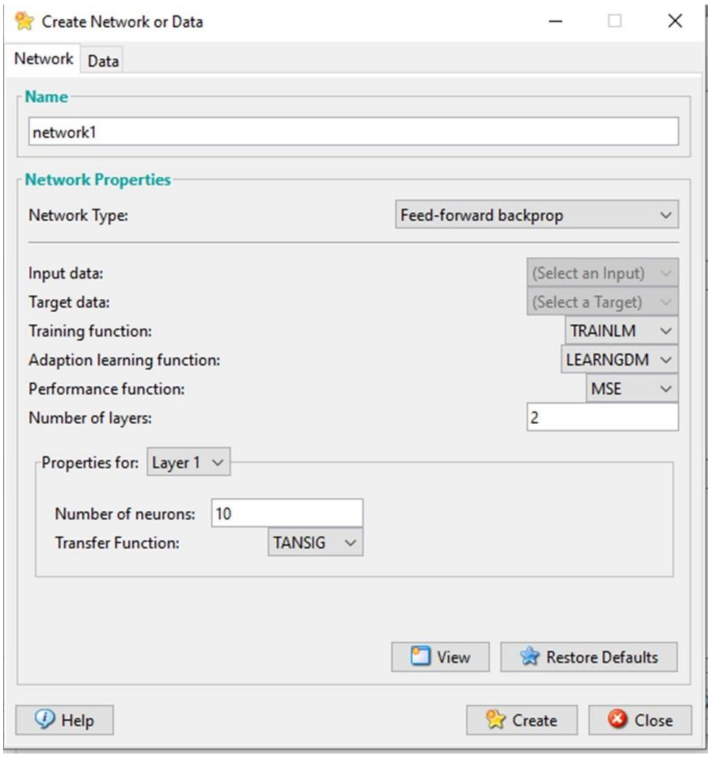


Figure 1: Training Model

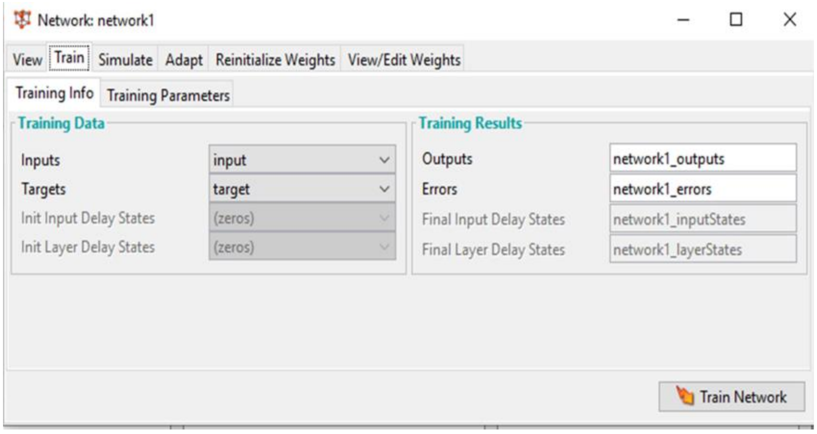


Figure 2: Training Parameters (a)

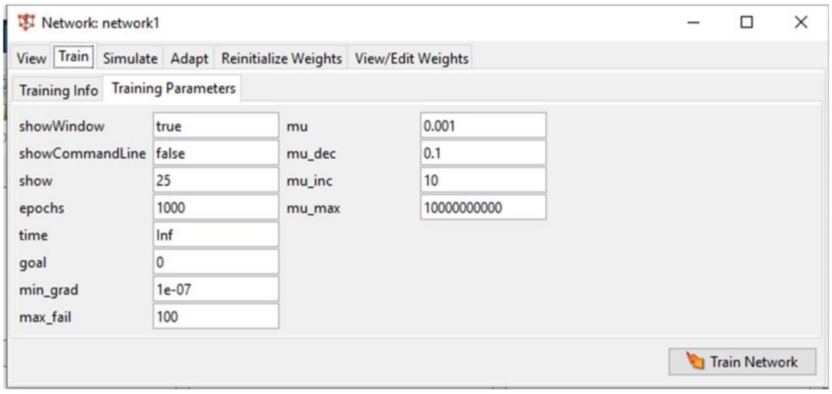


Figure 3: Training Parameters (b)

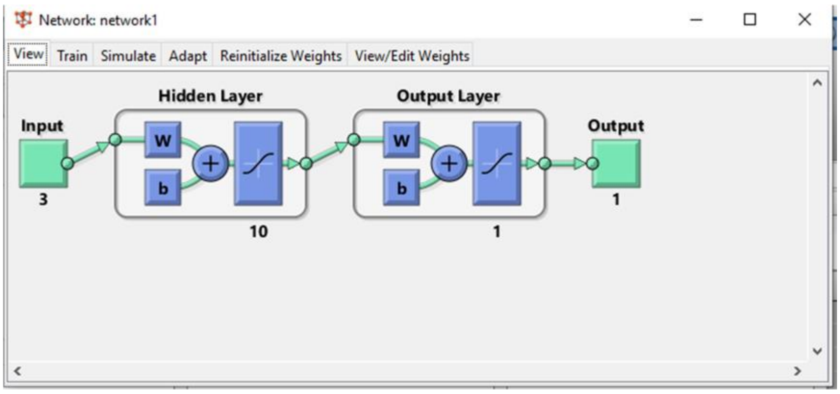


Figure 4: Network layout

A part factorial experimental design is analyzed through these networks. This part data is taken from the study Ranganath M. S. et al, Optimization of Process Parameters in Turning Operation of Aluminium (6061) with Cemented Carbide Inserts Using Taguchi Method and Anova" (Table 3, excluding column SURFACE ROUGHNESS, PREDICTED USING ANN and so obtained error)

Table 3: Surface roughness vs Various Parameters (2), (Result of the current paper analysis are shown in the last two columns)

Experiment No.	Speed	feed	D.O.C	Surface Roughness	Surface Roughness	Error	Surface Roughness	Error
	(RPM)	(mm/rev)	(mm)	(Experimental)	(Predicted using Taguchi)	(For Taguchi)	(predicted using ANN)	(For ANN)

1	1700	0.1	0.2	0.82000	0.822465	-0.00247	0.818295585	0.0017
2	1700	0.1	0.3	0.94000	0.923216	0.01678	0.911793873	0.0282
3	1700	0.1	0.4	0.96000	1.002099	-0.04210	1.122271101	-0.1623
4	1700	0.125	0.2	1.12000	1.044266	0.07573	1.109643469	0.0104
5	1700	0.125	0.3	1.06000	1.172187	-0.11219	1.078870298	-0.0189
6	1700	0.125	0.4	1.10000	1.272344	-0.17234	1.093152485	0.0068
7	1700	0.15	0.2	1.44000	1.269214	0.17079	1.398854224	0.0411
8	1700	0.15	0.3	1.54000	1.424692	0.11531	1.628816747	-0.0888
9	1700	0.15	0.4	1.50000	1.546424	-0.04642	1.505569303	-0.0056
10	1900	0.1	0.2	0.86000	0.7976	0.06240	0.935207618	-0.0752
11	1900	0.1	0.3	0.92000	0.895305	0.02470	0.944959392	-0.0250
12	1900	0.1	0.4	0.76000	0.971804	-0.21180	0.830790348	-0.0708
13	1900	0.125	0.2	1.04000	1.012696	0.02730	0.996550628	0.0434
14	1900	0.125	0.3	1.20000	1.13675	0.06325	1.182411498	0.0176
15	1900	0.125	0.4	1.10000	1.233879	-0.13388	1.105183523	-0.0052
16	1900	0.15	0.2	1.44000	1.230843	0.20916	1.33410015	0.1059
17	1900	0.15	0.3	1.60000	1.381621	0.21838	1.610717335	-0.0107
18	1900	0.15	0.4	1.50000	1.499672	0.00033	1.525684682	-0.0257
19	2100	0.1	0.2	0.88000	0.775869	0.10413	0.874857749	0.0051
20	2100	0.1	0.3	0.78000	0.870913	-0.09091	0.830881684	-0.0509
21	2100	0.1	0.4	1.16000	0.945327	0.21467	1.145021161	0.0150
22	2100	0.125	0.2	1.08000	0.985105	0.09490	1.00646358	0.0735
23	2100	0.125	0.3	1.14000	1.105779	0.03422	1.106886956	0.0331
24	2100	0.125	0.4	1.26000	1.200262	0.05974	1.248281393	0.0117
25	2100	0.15	0.2	0.58000	1.197309	-0.61731	0.664354686	-0.0844
26	2100	0.15	0.3	1.42000	1.343978	0.07602	1.201593158	0.2184
27	2100	0.15	0.4	1.86000	1.458814	0.40119	1.71640126	0.1436

The cutting speed, feed rate, and depth of cut are taken as input parameters and roughness values (Experimental) are taken as target parameters. The network was trained until the regression plot of the particular network fits the best possible ideal line. After the final training, the outputs & errors are recorded separately for each network.

III. SIMULATION

A sample data (Table 4) is fed to the network and the predicted surface roughness values from the NNTOOL are recorded for the network

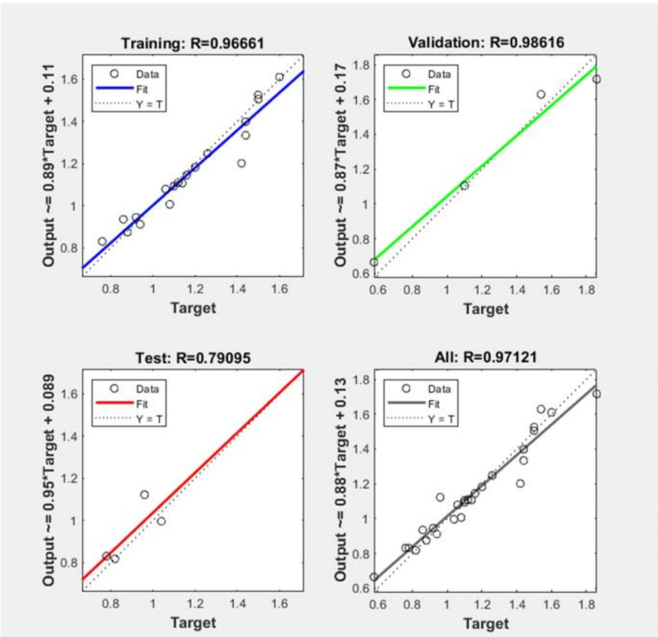
Table 4: Surface Roughness Prediction using Simulation NNTOOL

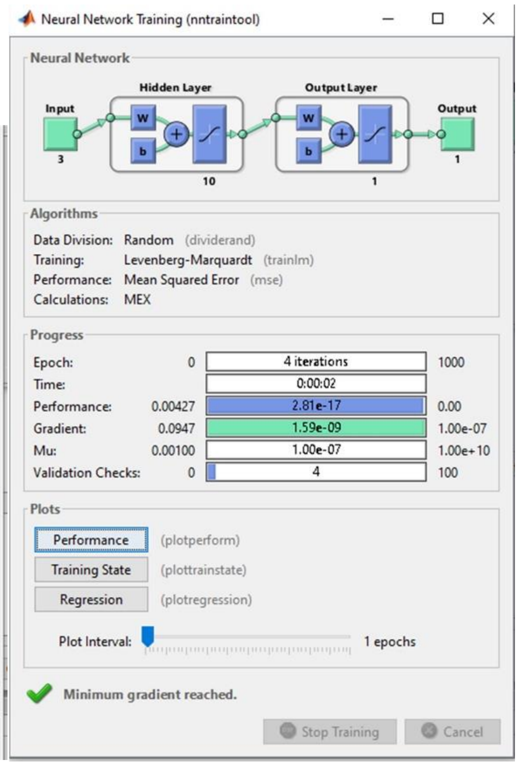
Experiment No.	Speed	feed	D.O.C	Surface Roughness(EXP)	Surface Roughness (Taguchi)	Error	Surface Roughness (Simulated using ANN)	Error3
1	1700	0.15	0.3	1.54000	1.424692	0.11531	1.6014	-0.0688
2	1700	0.15	0.4	1.50000	1.546424	-0.0464	1.50508	-0.0050
3	1900	0.1	0.2	0.86000	0.7976	0.06240	0.9022	- 0.04022

IV. RESULTS:

The present study serves two purposes. The first is to demonstrate the use of ANN in finding optimum values of surface roughness with given parameters. The second was to compare the results of those of Taguchi and ANN.

1. The output obtained is compared with the data used is given in table 2, with the following findings:
2. The mean error in the Taguchi principle was 12.58% whereas that in ANN is 5.11%
3. hence showing that the ANN tool is more efficient than Taguchi
4. It can also be seen that the results obtained from the ANN tool are highly reliable and showed very minute errors.
5. Predicted Values also were highly reliable showing a mean error of 3.80% only.
6. The regression model nearly fits the ideal line.





(5) (6)

Figure 5 and 6: Regression and training results

V. CONCLUSION:

1. With a neural network, designed with the parameters used in Table 2, accurate results can be obtained.
2. Although both the methods show very accurate results with minimum errors, still it can be seen the results obtained in ANN were much accurate than those obtained in Taguchi's.
3. By analyzing surface roughness values at different cutting parameters, an optimum cutting condition can be obtained using an optimum set of parameters where the value of surface roughness is minimum
4. The new methodology can be well adapted in the industry as it not requiring any major changes in the existing setup.

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